









# “Technical efficiency of Ukrainian pharmaceutical firms: Evidence from the COVID-19 pandemic and Russia-Ukraine war”

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<b>ARTICLE INFO</b>	Hanna Olasiuk, Prashant Sharma, Geetika Arora, Debi Prasad Satapathy and Sanjeev Kumar (2025). Technical efficiency of Ukrainian pharmaceutical firms: Evidence from the COVID-19 pandemic and Russia-Ukraine war. <i>Problems and Perspectives in Management</i> , 23(1), 703-716. doi: <a href="https://doi.org/10.21511/ppm.23(1).2025.52">10.21511/ppm.23(1).2025.52</a>
<b>DOI</b>	<a href="http://dx.doi.org/10.21511/ppm.23(1).2025.52">http://dx.doi.org/10.21511/ppm.23(1).2025.52</a>
<b>RELEASED ON</b>	Friday, 28 March 2025
<b>RECEIVED ON</b>	Monday, 30 December 2024
<b>ACCEPTED ON</b>	Monday, 17 March 2025
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<b>JOURNAL</b>	"Problems and Perspectives in Management"
<b>ISSN PRINT</b>	1727-7051
<b>ISSN ONLINE</b>	1810-5467
<b>PUBLISHER</b>	LLC “Consulting Publishing Company “Business Perspectives”
<b>FOUNDER</b>	LLC “Consulting Publishing Company “Business Perspectives”



NUMBER OF REFERENCES

44



NUMBER OF FIGURES

1



NUMBER OF TABLES

9

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## BUSINESS PERSPECTIVES



LLC "CPC "Business Perspectives"  
Hryhorii Skovoroda lane, 10,  
Sumy, 40022, Ukraine  
[www.businessperspectives.org](http://www.businessperspectives.org)

**Received on:** 30<sup>th</sup> of December, 2024

**Accepted on:** 17<sup>th</sup> of March, 2025

**Published on:** 28<sup>th</sup> of March, 2025

© Hanna Olasiuk, Prashant Sharma,  
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**Conflict of interest statement:**

Author(s) reported no conflict of interest

Hanna Olasiuk (India), Prashant Sharma (India), Geetika Arora (USA), Debi Prasad Satapathy (India), Sanjeev Kumar (India)

# TECHNICAL EFFICIENCY OF UKRAINIAN PHARMACEUTICAL FIRMS: EVIDENCE FROM THE COVID-19 PANDEMIC AND RUSSIA-UKRAINE WAR

**Abstract**

This paper examines the influence of marketing expenses and total assets on the technical efficiency of big Ukrainian pharmaceutical producers during the COVID-19 pandemic and the war in Ukraine. The data were collected from the nine leading pharmaceutical firms for six years, covering 2018–2023. Input-oriented data envelopment analysis was used, with revenue serving as the output and raw materials, sales, and general and administrative expenses as the inputs. The study found that the COVID-19 pandemic and the onset of the full-scale invasion of Russia in Ukraine caused a decline in efficiency, although not statistically significant. The analysis showed that around 70% of pharmaceutical firms need to increase the scale of operations to achieve efficiency. Additionally, smaller and older firms were found to have better efficiency. The research findings show that marketing productivity is positively associated with pure efficiency, while marketing expenses have the opposite impact with coefficients 0.064 and -0.05, respectively. Finally, a substantial increase in slacks during the COVID-19 pandemic propelled managers to find ways to cut sales and general and administrative costs. The results underscore the importance of cost optimization policies, along with asset and business-scale management in maintaining the efficiency of Ukrainian pharmaceutical firms.

**Keywords**

scale, slack analysis, marketing expenditures,  
pharmaceutical manufacturers, firm size

**JEL Classification**

L11, L25, M21

**INTRODUCTION**

Efficient utilization of firm resources is vital in firm performance. For pharmaceutical companies, the amount of marketing expenses, the value of firm assets, and the scale of operations determine efficiency. As practice shows, pharmaceutical companies spend hefty resources on marketing activities to keep a competitive advantage in the marketplace (Simanjuntak & Tjandrawinata, 2011; Moorman, 2016). If unchecked, elevated marketing expenses can hinder a firm's ability to maximize output with minimum resources. Scalability of business is another determinant of efficiency in the pharmaceutical industry. It stems from the ability of a firm to bargain in resource markets and maintain low per-unit costs. Big pharma firms maintain better profitability than smaller competitors (Mazumdar, 2013; Bhattacharyya & Chatterjee, 2020). Advances in non-parametric modeling allow one to measure firms' technical efficiency and identify its main determinants. To achieve the efficient frontier, managers are guided by efficiency scores on the magnitude of the cost-cutting interventions and changes needed in the marketing and financial areas of business.

While there is some solid evidence about the efficiency of foreign pharmaceutical firms, little is known about the technical efficiency of Ukrainian pharmaceutical manufacturers. The devastating effect of the COVID-19 pandemic, followed by the full-scale invasion of the Russian Federation in Ukraine on February 24, 2022, has taken a terrible toll on society. Increased need for medicines during wartime, supply chain disruption, and production facilities being in war zones spiraled into business inefficiencies. Given the challenging macroeconomic and geopolitical environment in which Ukrainian pharmaceutical firms operate, there is a pressing need to validate empirical evidence in the local context.

Since not all profitable companies are efficient, measuring firm efficiency can provide a distinct view of firm performance. This paper presents empirical evidence for the correlation between technical efficiency, marketing costs, and firm size in the Ukrainian pharmaceutical business. The study also adds to the understanding of the effects of the COVID-19 pandemic and the war on efficiency, as well as the link between overall, production and scale efficiency and returns to scale in Ukrainian pharmaceutical enterprises.

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## 1. LITERATURE REVIEW AND HYPOTHESES

Efficiency measures the level of firm performance that yields the maximum possible output with minimum inputs. Maintaining efficiency goes beyond profitability since the latter does not guarantee a firm's efficient utilization of resources. It is well-known that marketing expenses are a critical input and instrument of rivalry in the pharmaceutical business. Maintaining high marketing expenses has become a standard practice globally, with around 24.4% of sales in the USA and 30–50% in Europe (Gagnon & Lexchin, 2008). Empirical evidence corroborates with firm behavior, concluding the positive effect of marketing investments on company performance (Park et al., 2009; Suh et al., 2011; Wang & Wu, 2012; Caglar & Nisel, 2017). Another piece of evidence points to the non-linear behavior of marketing investments with respect to firm size: they improve the profitability of small firms and diminish the profits of big companies (Ryoo et al., 2016; Jaisinghani & Kanjilal, 2019). While the relationship between marketing costs, profitability, and revenue has been studied relatively well, the link between marketing expenses and technical efficiency is yet to be explored.

The effect of size on firm efficiency has been thoroughly studied in manufacturing, especially in the pharmaceutical sector. Efficiency and company size are correlated, but this link depends on the sector and country of origin, underscoring the importance of the competitive and regulatory environment in which companies operate. Notably,

the German manufacturing sector has a U-shaped connection between size and efficiency, with small and big companies being more efficient than their medium-sized competitors (Schiersch, 2013). On the contrary, a study of manufacturing firms in Africa established a positive relationship among variables for small companies and a negative one for big firms due to the difference in the regulatory environment (Aggrey et al., 2010). In a study of European pharmaceutical companies, big firms are confirmed to have higher efficiency than small and medium-sized ones (Díaz & Sanchez-Robles, 2020). Larger companies are typically more efficient than smaller ones in the Indian pharmaceutical industry (Mazumdar & Rajeev, 2009). Mazumdar (2013) provided additional evidence supporting the notion that firm size affects efficiency and proposed policy changes to mitigate size inefficiencies through mergers and acquisitions and public-private partnerships.

Mahajan et al. (2018) also empirically proved non-linear relationships between pure efficiency and firm size, whereby size positively impacted efficiency. However, further growth in total fixed assets will lead to diseconomies to scale. Thus, the efficiency of small firms can be enhanced through mergers and acquisitions or engagement in contract manufacturing. Bhattacharyya and Chatterjee (2020) confirm high technical efficiency levels for big pharmaceutical companies. Concurrently, they argue that medium and small companies are more efficient in India. Thus, the size of operations requires thorough monitoring.

The accuracy and comparability of efficiency scores depend highly on the estimation methods and selected input-output mix. Efficiency scores can be used as a standalone measure for competitive benchmarking or as the dependent variable for subsequent analysis. For example, Saranga and Phani (2009) identified the primary determinants of efficiency in the Indian pharmaceutical sector from 1992 to 2002. The influence of ownership type, age, and R&D activities on the efficiency of pharmaceutical producers was also distinguished using the efficiency scores. In the 2010–2011 financial year, Mahajan et al. (2014) investigated the technical efficiency of 50 Indian pharmaceutical producers. They subsequently expanded their analysis to include a panel of 141 Indian pharmaceutical companies from 2000 to 2013 (Mahajan et al., 2018). The Product Patent Act's implementation, size, age, ownership, capital import intensity, and pure efficiency were investigated. In a comparable manner, Pannu et al. (2011) investigated how Indian pharmaceutical businesses' productivity and efficiency changed between 1998 and 2007. They proved that productivity improvements have resulted from the pharmaceutical industry's increased efficiency in India. Capital, labor, and raw materials costs are used as inputs, while revenue is the output in all three articles.

A slightly different set of inputs can be found in the studies of the efficiency of Bangladeshi (Azad et al., 2018) and Nigerian (Obukohwo et al., 2018) pharmaceutical firms, where, among others, technical efficiency is measured using the cost of sales, fixed capital, and operating expenses. Another study of the European pharmaceutical companies estimated the trends in efficiency during 2010–2018. The output is captured through turnover in real prices, while inputs are taken as the number of workers and adjusted for inflation total assets. The results confirmed that firms engaged in R&D have lower levels of efficiency than manufacturers. The overall trend is that efficiency is declining for all firms. The results indicate that efficiency negatively correlates with personnel costs and positively correlates with profit margins, cash flow, and collection period. Another important implication is that a country of origin significantly impacts firm efficiency (Díaz & Sanchez-Robles, 2020).

The resource-based theory attributes the firm's performance to its resources' productivity (Makadok,

2001). Firm performance is associated with various functional capabilities, including marketing ones (Vorhies & Morgan, 2003; Nath et al., 2010), to transform resources productively (Krasnikov & Jayachandran, 2008). Currently, practitioners employ a mix of marketing ratios to assess firm performance. In the early 1970s, marketing performance was measured through productivity as a ratio of sales to advertising (sales) expenditures. The prevailing focus was on financial and accounting goals, which gave a clear understanding of the most productive business segments. Thus, applying accounting in marketing enabled companies to allocate marketing resources more efficiently (Bonoma & Clark, 1988). Another metric that helps evaluate marketing efficiency is the returns on marketing investments (ROMI). It is calculated as the net profit (revenue) to marketing costs ratio. ROMI allows one to prioritize marketing activities, capture the results of marketing efforts, as well as better plan, communicate and execute marketing projects (Powell, 2002). An apparent drawback of this parameter is that the value of ROMI can be artificially inflated by reducing marketing expenditures. Therefore, marketing managers might be rewarded for non-existing marketing success (Duffy, 2002; Ambler, 2003; Kumar & Petersen, 2004).

A more broad-based indicator of marketing performance is the ratio of sales, general, and administrative costs to sales (SGAC/S), which can be applied to the analysis of business and consumer markets (Foster & Gupta, 1994). Additionally, it provides a fair representation of the effectiveness of marketing and other administrative departments within an organization. According to Bontis (1988), sales, general, and administrative costs are proxies for measuring relational capital (RC) – investments necessary to maintain relationships with stakeholders and clients. A regression analysis of relational capital revealed its positive effect on all profitability indicators: ROE, ROI, and ROA (Scafarto et al., 2016). Various measures of relational capital across countries and in different industries have come to the same result: proven positive contribution of RC to a company's market value and corporate performance (Veltri, 2008). According to Jaisinghani and Kanjilal's (2019) estimates, marketing expenditures improve the performance of small businesses, although found det-

perimental to the performance of large corporations. For a threshold panel regression analysis, marketing expenditures were measured as a ratio of marketing expenses to sales, firm performance was assessed through ROA, while a natural logarithm of total assets was used to calculate the firm's size.

The aim of this paper is to establish the relationship between marketing expenditure and productivity metrics, total assets, firm age and technical efficiency of the leading Ukrainian pharmaceutical manufacturers.

The reviewed literature underscores the importance of marketing expenditures and size to firm efficiency. Updated evidence on the factors contributing to the efficiency of firms will enable better decision-making and lead to optimal utilization of resources. The hypotheses of the study are as follows:

- H1: *Marketing expenses negatively affect pure efficiency.*
- H2: *Marketing productivity positively affects firm efficiency.*
- H3: *There is a positive relationship between efficiency, firm size, and firm age.*

## 2. METHODS

This study uses 2-stage input-oriented data envelopment analysis (DEA) to calculate technical efficiency for nine leading pharmaceutical manufacturers in Ukraine. The estimation model ranks firms from the most efficient to the least efficient, providing the scores for overall, pure, and scale efficiency. Additionally, the study provides firm-

wise returns to scale, along with slacks, giving the targets for potential input reduction. Finally, efficiency scores were tested for stability using Spearman rank correlation. After obtaining efficiency scores, the analysis ran the Tobit regression model to estimate the impact of marketing expenses, marketing productivity, ROMI, firm size, age, the COVID-19 pandemic, and the war on firm efficiency (Table 1). The firms account for more than 50% of sales of all Ukrainian manufacturers; thus, the sample represents the activity of local manufacturers well. Data were handpicked from the corporate financial statements available on the official websites of respective companies and the web portal of the Stock Market Infrastructure Development Agency of Ukraine and Youcontrol Agency. The limited availability of open financial data on Ukrainian pharmaceutical manufacturers has restricted the number of variables considered for the current analysis. To examine the technical efficiency of nine major national manufacturers, two inputs and one output were selected, with raw materials and sales, general and administrative costs representing input, and revenue representing output variables.

Technical efficiency was assessed using the methods outlined by Mahajan et al. (2014, 2018), who examined the efficiency of Indian pharmaceutical companies. The study picked net revenue as an output, raw materials costs, salaries and wages, advertising and marketing expenses, and capital usage costs as inputs. Since there was a limited panel of data covering six years and nine companies, the study chose only two inputs and one output. The following rules have been applied to select the correct number of variables. First, the sum of the inputs and outputs cannot be greater than the total number of DMUs. Second, there must be three times as few inputs and outputs as there are

**Table 1.** List of variables used in the study

Purpose	Variable	Explanation
Efficiency analysis	Output	Revenue
	Input	Sales, general and administrative costs (SGAC) Raw materials
Tobit regression	ROMI	Share of net profit to marketing expenses
	Marketing productivity (Sales/ME)	The ratio of sales to marketing expenses
	ME/TE	Share of marketing expenses in total expenses
	Firm size	Natural log of the firm's assets
	Firm age	Difference between current and inception year
	COVID-19 and war dummies	Pre-, during, and post-COVID-19 periods, before and during war



DMUs. Five OLS regressions have been constructed to identify the two most influential inputs. The OLS models used revenue as a dependent variable and marketing expenses, raw material costs, wages and salaries, sales, and general and administrative costs as explanatory variables. Revenue is an output of the DEA analysis, together with sales, general and administrative expenses, and the cost of raw materials as inputs.

DEA entails a deterministic, non-parametric linear modeling approach to assessing the technical efficiency frontier of DMUs. The technique has the following advantages: it may be used with a small sample size; it does not require the pricing of products or resources; it does not require the construction of a production function form; it allows for many inputs and outputs; it provides efficiency scores and rankings of DMUs. On the contrary, some drawbacks of the DEA model are associated with the sensitivity of efficiency scores to the selection of inputs and outputs. Besides, the number of inputs and outputs must fit the criteria to prevent an unjustified growth in the number of efficient units. This study uses two models, namely, CCR, which operates under the premise of constant returns to scale (Charnes et al., 1978), and the BCC model, which estimates the efficiency based on variable returns to scale (Banker et al., 1984). These models have gained much recognition in efficiency analysis. The CCR model aims to assess overall technical efficiency arising due to efficient production and scale. The BCC model calculates efficiency scores based on the production/pure efficiency of DMUs. According to BCC analysis, inefficiencies can be eliminated by subsequent optimization of the input/output mix. Scale efficiency (SE) is obtained as a ratio of overall to pure efficiency. A scale efficiency score of less than 1 signals inefficiencies that arise from a firm's scale and require managerial interventions.

Equations 1-3 represent the input-oriented CCR model, while Equations 4-6 mathematically describe BCC model.

Input-oriented CCR (envelopment) model:

$$\text{Min}Z_k = \phi_k - \varepsilon \left( \sum_{i=1}^m s_{ik}^+ + \sum_{j=1}^s s_{jk}^- \right) \quad (1)$$

Subject to:

$$\begin{aligned} \sum_{r=1}^n \lambda_{rk} y_{ir} - s_{ik}^+ &= y_{ik} \quad \forall i = 1, \dots, m, \\ \sum_{r=1}^n \lambda_{rk} x_{rj} + s_{jk}^- &= \phi_k x_{jk} \quad \forall j = 1, \dots, s, \\ \lambda_{rk} &\geq 0 \quad \forall r = 1, 2, \dots, n, \end{aligned} \quad (2)$$

$\phi_k$  is unrestricted is sign

$$s_{jk}^-, s_{ik}^+ \geq 0 \quad \forall j = 1, 2, \dots, s, \quad i = 1, 2, \dots, m, \quad (3)$$

Input-oriented BCC (envelopment) model:

$$\text{Min}Z_k = \phi_k - \varepsilon \left( \sum_{i=1}^m s_{ik}^+ + \sum_{j=1}^s s_{jk}^- \right), \quad (4)$$

Subject to:

$$\begin{aligned} \sum_{r=1}^n \lambda_{rk} y_{ir} - s_{ik}^+ &= y_{ik} \quad \forall i = 1, \dots, m, \\ \sum_{r=1}^n \lambda_{rk} x_{rj} + s_{jk}^- &= \phi_k x_{jk} \quad \forall j = 1, \dots, s, \\ \sum_{r=1}^n \lambda_{rk} &= 1 \quad \forall r = 1, 2, \dots, n, \end{aligned} \quad (5)$$

$\phi_k$  is unrestricted in sign, and

$$\lambda_{rk}, s_{jk}^-, s_{ik}^+ \geq 0 \quad \forall r, j, i, \quad (6)$$

where  $\text{Min} Z_k$  represents the input-oriented efficiency of  $k^{\text{th}}$  DMU according to CCR and BCC models.  $s_{ik}^+$  denotes the slack in  $i^{\text{th}}$  output and  $s_{jk}^-$  represents the slack in the  $j^{\text{th}}$  input for the  $k^{\text{th}}$  DMU. The CCR and BCC models aim to determine the maximum possible reduction in inputs for  $k^{\text{th}}$  DMU without altering the reference technology. The constraints (ii) and (iii) define the convex reference technology. The following condition indicates the non-negativity of the slacks:  $s_{ik}^+, s_{jk}^- \geq 0$ . This equation is used to compute the efficiencies of  $k$  DMU's. If  $\phi_k = 1$ , the  $k^{\text{th}}$  DMU is considered Pareto efficient, meaning all slacks i.e.  $s_{ik}^+$  and  $s_{jk}^-$  are zero for every  $i$  and  $j$ . These Pareto efficient DMUs lie on the efficient frontier with either input or output orientation.

### 3. RESULTS AND DISCUSSION

A resilient and competitive pharmaceutical manufacturing sector constitutes a critical component of economic stability for a developing nation such as Ukraine. The Ukrainian pharmaceutical mar-

ket is widely recognized for its substantial profitability, with sales experiencing consistent annual growth rates of 15–20% over the past five years. Notably, Ukrainian pharmaceutical manufacturers contribute 0.5% to the overall national industrial output. Furthermore, the pharmaceutical industry stands out as the second most lucrative sector, boasting an impressive operating margin of 16.5%, surpassed only by the mining industry. Unfortunately, over the past decade, the number of entities engaged in drug manufacturing witnessed a decline of 27.7%, reducing from 307 to 222 firms. This downturn disproportionately impacted small and micro firms within the industry, resulting in a 20.3% and 53.3% closure rate, respectively. Approximately 30% of pharmaceutical companies annually report financial losses (Olasiuk et al., 2020).

The adverse macroeconomic and political environment has constantly challenged the performance of the Ukrainian pharmaceutical business. Such factors as a political crisis, military aggression of the Russian Federation, extreme currency volatility, galloping inflation, expensive borrowing costs, and negative credit rating led to tempo-

rary exports shrinking and collapse in small businesses. Despite various economic upheavals, the 10 major manufacturers displayed double-digit revenue growth, exhibiting minimal indications of financial distress (Olasiuk et al., 2020; SMIDA, 2022). Top national leaders in pharmaceutical production have significant variability in their size and marketing performance metrics. Table 2 illustrates the summary statistics on the number of employees, the share of marketing expenditures in total expenses (ME/TE), the share of sales, general and administrative costs in sales (SGAC/Sales), returns on marketing investments (Net Profit/ME), and the marketing productivity (Sales/ME) of the firms during 2018–2023. The analysis covers three distinct periods: before the COVID-19 pandemic (2018–19), during the pandemic (2020–2021), and post-pandemic/onset of war (2022–2023).

The mean number of employees has been growing throughout the entire period, showing a noticeable drop in 2023. All marketing metrics of pharmaceutical firms fluctuated, with SGAC/Sales, ROMI, and marketing productivity registering an all-time high in 2023. On average, companies spend between 21–24% of their total expenses on

**Table 2.** Descriptive statistics of Ukrainian pharmaceutical firms during 2018–2023

Year	2018	2019	2020	2021	2022	2023
<b>Mean</b>						
N_Employees	1,124.44	1,138.67	1,151.78	1,160.22	1,099.33	1,030.22
ME/TE	21.72	23.84	22.70	24.11	21.31	22.19
SGAC/Sales	27.79	28.16	25.18	29.07	28.14	30.03
ROMI	0.35	0.51	0.39	0.32	0.61	1.05
MKT_Productivity	6.02	5.86	6.55	5.79	8.47	15.69
<b>Minimum value</b>						
N_Employees	336.00	358.00	398.00	399.00	364.00	338.00
ME/TE	8.36	10.21	6.70	9.65	4.31	1.27
SGAC/Sales	13.57	12.00	9.23	12.87	8.97	8.86
ROMI	-0.08	0.08	-0.50	-0.21	-0.33	0.06
MKT_Productivity	3.56	3.15	3.15	3.05	3.36	3.36
<b>Maximum value</b>						
N_Employees	2,560.00	2,698.00	2,761.00	2,889.00	2,625.00	2,610.00
ME/TE	31.36	33.67	33.74	35.02	31.16	32.47
SGAC/Sales	32.54	35.44	38.92	39.99	38.69	42.30
ROMI	0.78	0.88	1.26	1.07	1.83	6.48
MKT_Productivity	12.96	14.48	15.88	14.36	34.24	101.53
<b>Standard deviation</b>						
N_Employees	677.91	703.47	711.96	746.48	674.27	669.12
ME/TE	7.25	7.80	9.74	8.40	9.17	10.12
SGAC/Sales	6.05	7.87	10.32	7.87	9.16	10.90
ROMI	0.30	0.31	0.58	0.45	0.65	2.07
MKT_Productivity	2.87	3.50	4.23	3.44	9.80	32.24

marketing. The onset of the pandemic, followed by the full-scale invasion of the Russian Federation in Ukraine, exacerbated the gap in the capacity of firms to invest in marketing. The standard deviation in marketing metrics has been on the rise and reached its peak in 2023. Marketing productivity is highly unequal among firms: 1 UAH of marketing expenditures generates between 3.05 to 101.53 UAH of sales, with an average indicator ranging between 5.79 and 15.69 UAH. Increasing variability is also noticeable in SGAC expenditures, with a maximum value of 42.3% and a minimum of 8.86% of sales as of 2023. Compared to a low pre-pandemic base, returns on marketing investments have jumped from 0.32 UAH in 2021 to 0.61 UAH in 2022 and 1.05 UAH in 2023, respectively.

Correlation and regression output for the primary cost variables affecting sales were conducted to check the impact of sales and marketing costs on revenue. Five regression models were constructed to avoid multicollinearity among independent variables. Table 3 presents correlation results, while Table 4 displays the regression output for four distinct models providing the relationship between revenue and potential inputs. Further, the variance

inflation factor (VIF) was employed to identify possible multicollinearity. In four models, VIF was within the permissible range of less than 10.

All regression models have significant explanatory power and can be used to predict firms' revenues. Considering potential adjustments in the output, it appears more feasible to alter the utilization of raw materials through bargaining and managerial decisions. On the contrary, wages are sticky and tend to move once market conditions change; thus, it is unlikely that the firm will make a unanimous decision about salary cuts. Additionally, SGAC inputs provide managers with more leverage for optimization. Subsequently, DEA analysis will consider SGAC and raw materials as inputs. Further, the study investigates the possibility of input and scale optimization through the reduction of marketing and sales costs and altering the scale of the business.

The results of the DEA analysis show significant disparity among Ukrainian pharmaceutical companies. Table 5 summarizes the overall (OTE), production/pure (PE), and scale (SE) efficiency scores and returns to scale for the top nine pharmaceutical manufacturers over six years.

**Table 3.** Correlations between inputs and output

Variables	(1)	(2)	(3)	(4)	(5)
(1) Revenue	1.000	–	–	–	–
(2) Marketing costs	0.912	1.000	–	–	–
(3) SGAC	0.965	0.975	1.000	–	–
(4) Raw materials	0.958	0.890	0.910	1.000	–
(5) Wages and Salaries	0.951	0.814	0.893	0.880	1.000

**Table 4.** Regression output

Variables	(1)	(2)	(3)	(4)	(5)
	Revenue	Revenue	Revenue	Revenue	Revenue
Marketing costs	1.359*** (.375)	1.967*** (.23)	–	–	–
Raw materials	2.17*** (.24)	–	1.442*** (.184)	–	1.66*** (.158)
Wages and Salaries	–	3.289*** (.256)	–	2.347*** (.288)	2.531*** (.273)
SGAC	–	–	1.666*** (.186)	1.771*** (.168)	–
cons	–348.254** (141.678)	192.873* (96.635)	–152.201 (102.487)	276.524*** (81.109)	–154.734 (100.248)
Observations	54	54	54	54	54
R-squared	.935	.96	.968	.97	.97
RMSE	588.656	460.842	411.351	402.738	403.103
Adj R <sup>2</sup>	.933	.959	.967	.969	.968
VIF	9.75	5.12	11.26	7.66	8.63

Note: Standard errors are in parentheses. \*\*\*  $p < .01$ , \*\*  $p < .05$ , \*  $p < .1$ .



**Table 5.** Firm trends in efficiency and returns to scale

Company	Mean			Minimum value			Returns to Scale		
	OTE	PE	SCALE	OTE	PE	SCALE	CRS	DRS	IRS
Borshchahivskiy CPP	0.90	0.92	0.97	0.78	0.80	0.95	0	1	5
Darnitsa	0.93	0.95	0.97	0.86	0.90	0.89	1	3	2
Farmak	0.99	1.00	0.99	0.95	1.00	0.95	5	1	0
Galychpharm	0.92	0.94	0.98	0.75	0.77	0.93	3	1	2
Indar	0.69	1.00	0.69	0.52	1.00	0.52	0	0	6
Kyiv Vitamin Factory	0.72	0.73	0.99	0.67	0.67	0.96	0	2	4
Kyivmedpreparat	0.78	0.81	0.96	0.69	0.72	0.91	0	3	3
Lekhim	0.86	1.00	0.86	0.74	1.00	0.74	1	0	5
Zdorovyе	0.97	1.00	0.97	0.84	1.00	0.84	5	1	0
Average	0.86	0.93	0.93	0.52	0.67	0.52	15	12	27
Kruskal-Wallis test	0.000	0.000	0.000	–	–	–	–	–	–

According to the CCR model, Farmak is a leader in overall technical efficiency, followed by Zdorovyе and Darnitsa, which need to improve their efficiency by a mere 3% and 7%, respectively. The laggard is Kyiv Vitamin Factory, with OTE ranging between 72% and 67%, and Indar showing a mean OTE of 69% and a minimum of 52%. The former faces inefficiency due to the low input utilization, and the latter has an issue with the scale of operations. As per the BCC model, four firms appeared purely efficient, indicating their ability to 100% efficiently convert inputs into output with further scale optimization. Among them are Farmak, Indar, Lekhim and Zdorovyе. The poorest input management has Kyiv Vitamin Factory with an average PE of 73% and Kyivmedpreparat – 81%, leaving massive scope for efficiency improvement. Under the DEA analysis, a scale less than 1 implies the negative impact of company size on its efficiency. Therefore, companies need to consider improving the scale of operations by 7% on average. Industry-average OTE is 86% and can be improved by 14% through scale optimization and sound resource management practices. Given the firm's size, the PE of pharmaceutical companies is larger than OTE, with an average of 0.93. Approximately 7% improvement can be reached through better input management without any decrease in output.

The Kruskal-Wallis test confirmed statistically significant heterogeneity in the technical efficiency of the nine largest pharmaceutical manufacturers. Data from Table 5 stressed the skewness of returns to scale of pharmaceutical companies. Out of 54 firm-year observations, 27 times (50%) companies operated under increasing returns to scale,

15 times (28%) under constant returns to scale, and 12 times (22%) – under decreasing returns to scale. In the sample, Farmak and Zdorovyе have five years of operations under constant returns to scale; Darnitsa and Kyivmedpreparat showed three years of decreasing returns to scale and recommended downsizing their production activities. Lastly, Indar bottoms the rank due to its inappropriate business scale, with six years of operations under increasing returns, followed by Lekhim and Borshchahivskiy CPP, which have showcased increasing returns for five years. The analysis confirms that some profitable companies lack efficiency, as Cooper et al. (2007) suggested.

Further, the study analyzed efficiency trends in the Ukrainian pharmaceutical industry. As Table 6 features, a significant decline in OTE, PE, and SE occurred in 2020 – a peak of the COVID-19 pandemic, resulting in supply bottlenecks and a nationwide and global slowdown in business activity. Post-COVID-19 efficiency indicators have recuperated, although not enough compared to the pre-pandemic levels. The post-COVID-19 period coincided with the onset of war in Ukraine, which brought about massive devastation to the physical and human capital of the country and many businesses nationwide. Another aspect of the differences in firm efficiency is the returns to the scale in which they operate. Firms with DRS operate at 95% scale efficiency, while IRS firms operate at 89% only. On the other hand, IRS firms have better resource management practices, allowing them to utilize inputs with 91% efficiency compared to 88% in DRS firms. Kruskal-Wallis test confirms that efficiency changes during the COVID-19 pandemic and the start of the war were

**Table 6.** Efficiency trends in Ukraine's pharmaceutical industry

Year	Mean			Minimum value			Standard deviation		
	OTE	PE	SCALE	OTE	PE	SCALE	OTE	PE	SCALE
2018	0.89	0.94	0.95	0.76	0.80	0.76	0.09	0.08	0.08
2019	0.89	0.94	0.95	0.64	0.74	0.64	0.13	0.09	0.12
2020	0.80	0.90	0.89	0.52	0.72	0.52	0.15	0.12	0.16
2021	0.88	0.94	0.93	0.68	0.70	0.72	0.13	0.11	0.10
2022	0.86	0.93	0.93	0.67	0.70	0.70	0.13	0.11	0.09
2023	0.87	0.92	0.94	0.67	0.67	0.81	0.11	0.11	0.07
Kruskal-Wallis test	0.82	0.99	0.83	–	–	–	–	–	–
Pre-COVID-19	0.89	0.94	0.95	0.64	0.74	0.64	0.11	0.08	0.10
During COVID-19	0.84	0.92	0.91	0.52	0.70	0.52	0.14	0.12	0.13
Post- COVID-19	0.86	0.93	0.94	0.67	0.67	0.70	0.12	0.11	0.08
Kruskal-Wallis test	0.56	0.98	0.47	–	–	–	–	–	–
Before war	0.864	0.931	0.931	0.523	0.695	0.523	0.128	0.101	0.117
During war	0.865	0.926	0.936	0.669	0.670	0.704	0.116	0.111	0.082
Kruskal-Wallis test	0.93	0.86	0.55	–	–	–	–	–	–
DRS	0.83	0.88	0.95	0.67	0.70	0.84	0.09	0.11	0.05
IRS	0.80	0.91	0.89	0.52	0.67	0.52	0.11	0.11	0.13
Kruskal-Wallis test	0.000	0.000	0.000	–	–	–	–	–	–

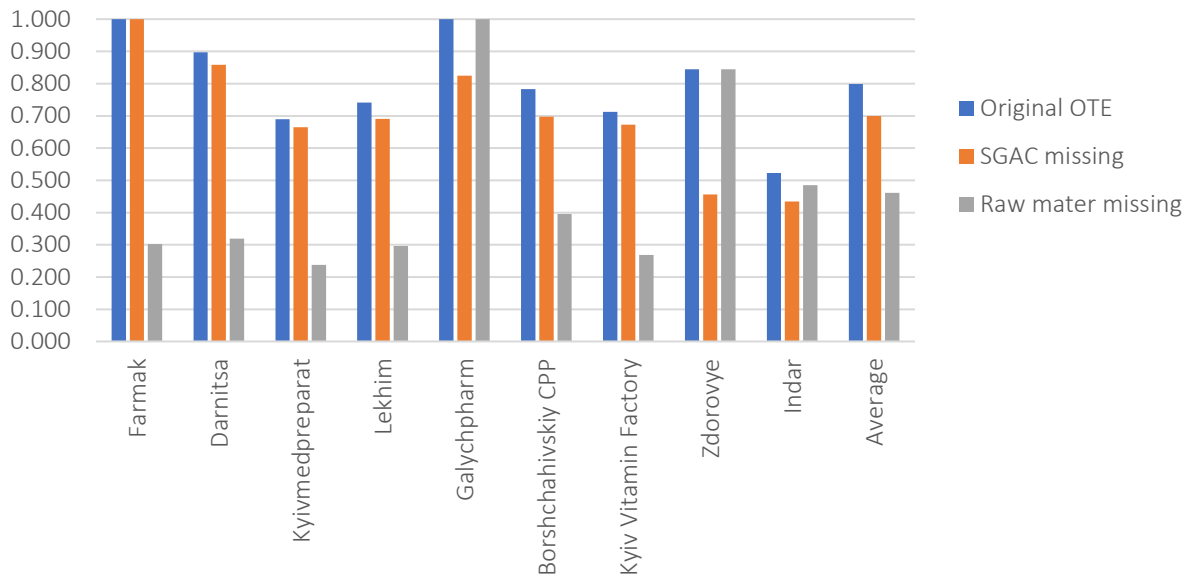
Note: DRS – decreasing returns to scale, IRS – increasing returns to scale.

negative; however, they were not statistically significant. Firm-level variability in returns to scale defined statistically significant differences in OTE, PE, and SE efficiency.

Slacks display an optimal reduction in input, which would not lead to respective output reduction. According to BCC analysis, in 2018–2019, input slacks were negligible in the pharmaceutical industry. However, in 2020, the pandemic changed the business scenario, and four firms were advised to cut sales and general and administrative costs. Remarkably, Darnitsa was advised to reduce SGAC by 3.2 million UAH, Kyivmedpreparat – by 144 million, Borshchahivskiy CPP – by 45 million, and Kyiv Vitamin Factory – by 74 million UAH. In the following 2021, Darnitsa had to cut 188 million UAH. Kyivmedpreparat had significant SGAC slacks in 2021–2022, amounting to 64 and 4.6 million UAH, respectively. Indar is the least efficient firm on the list and requires revenue improvement. Its output slack in 2020 comprised almost 524 million UAH, and in 2022 decreased to 290 million UAH, meaning that the company should increase its sales to become efficient. Slack analysis of inefficient firms displays a persistent issue with sales costs. These costs are drivers of revenues and are often difficult to manage. Due to a lack of expertise and culture around marketing, local pharmaceutical businesses prioritize the sales function, with

a greater emphasis on sales and distribution than their international rivals (Goncharuk & Getman, 2014). Thus, cutting the resources devoted to sales and administrative functions and channeling them to develop marketing capabilities, processes, and departments can substantially improve efficiency. With a few exceptions, firms have no difficulty managing raw materials.

Next, the study estimated the stability of efficiency scores using the efficiency scores of 2020. The procedure involves the Jackknifing technique, based on the sequential exclusion of the most efficient DMUs with subsequent recalculation of efficiency scores. The method has been successfully used by Mahajan et al. (2014) and Mostafa (2007). After calculating technical efficiency scores, Spearman rank correlation coefficients are obtained. Efficiency scores are considered stable if the correlation coefficients are high. There are, however, other methods to validate the power of efficiency scores: regressing efficiency scores to some of the external company parameters, like size, ownership, intensity of R&D, firm age, intensity of exports, and capital imports intensity (Saranga & Phani, 2009; Mahajan et al., 2018), using Tobit regression or two-stage bootstrapping, which is considered as more advanced techniques (Simar & Wilson, 2007; Badunenko & Tauchmann, 2019).



**Figure 1.** Impact of omitted variables on the OTE

**Table 7.** Spearman’s rank correlation coefficients

Variables	1	2	3	4	5	6
(1) theta_1	1.000	–	–	–	–	–
(2) theta_2	0.272	1.000	–	–	–	–
(3) theta_3	0.272	1.000	1.000	–	–	–
(4) theta_4	0.272	1.000	1.000	1.000	–	–
(5) theta_5	0.272	1.000	1.000	1.000	1.000	–
(6) theta_6	0.056	0.816	0.816	0.816	0.816	1.000

Spearman rank correlation is 0.816, which testifies the validity and stability of efficiency scores (Table 7). These findings are identical to those obtained by Donthu et al. (2005), who also established a negligible impact of missing variables on efficiency.

Further drawing from Donthu et al. (2005), the effect of omitted variables on the overall efficiency of nine DMUs was estimated. As presented in Figure 1, the exclusion of either input yields lower efficiency. The results are susceptible to the elimination of raw material inputs, wherein the efficiency decreased from an initial 0.799 to 0.461. The correlation between initial OTE and OTE after removing raw materials from the DEA analysis is 0.368. The identical correlation with sales and general and administrative costs is 0.757. Additionally, the effect of missing variables on PE was tested. The initial average PE of 0.905 dropped to 0.819 and 0.719 after the sequential exclusion of SGAC and raw materials, respectively. Contrary to OTE,

pure efficiency scores are highly sensitive to the exclusion of SGAC, with a registered correlation of 0.289. Hence, the analysis suggests the importance of both inputs for the accurate calculation of the overall and pure efficiencies for Ukrainian pharmaceutical firms.

Further, a set of Tobit regression models was run to check the impact of marketing expenses as a share of total expenses, marketing productivity, and ROMI on companies’ pure efficiency. The analysis confirmed the hypotheses about the negative relationship between marketing expenses, firm size, and efficiency. The results found that marketing expenses have a negative impact, and marketing productivity positively impacts PE. No relationship between marketing metrics and OTE was found. Given the limited available data, the Tobit regression included three additional regressors: firm size, square firm size, and age.

It was found that total assets negatively affect firms’ efficiency in the pharmaceutical industry. However, the effect becomes positive once companies double in size. Such an outcome is not surprising, given the predominance of companies with increasing returns to scale. The results align with microeconomic theory, which posits that, normally, larger companies display greater efficiency due to better utilization of marketing, administrative, logistical, material, and human resources

**Table 8.** Tobit regression

PE	Coef.	Std.Err.	t-value	p-value	[95% Conf Interval]	Sig
Firm Size	-7.301	2.799	-2.61	.012	-12.924 -1.679	**
Square Firm Size	.248	.095	2.62	.012	.058 .439	**
ROMI	.066	.044	1.48	.145	-.023 .154	-
Age	.007	.005	1.45	.153	-.003 .016	-
Constant	54.374	20.636	2.63	.011	12.926 95.822	**
Pseudo r-squared	1.066		Number of obs		54	
Chi-square	33.418		Prob > chi2		0.000	
Akaike crit. (AIC)	9.927		Bayesian crit. (BIC)		21.861	
PE	Coef.	Std.Err.	t-value	p-value	[95% Conf Interval]	Sig
Firm Size	-8.067	2.73	-2.95	.005	-13.551 -2.582	***
Square Firm Size	.275	.092	2.99	.004	.09 .46	***
ME/TE	-.015	.003	-5.03	0	-.021 -.009	***
Age	.006	.003	1.87	.067	0 .012	*
Constant	60.236	20.227	2.98	.004	19.608 100.863	***
Pseudo r-squared	1.932		Number of obs		54	
Chi-square	60.568		Prob > chi2		0.000	
Akaike crit. (AIC)	-17.223		Bayesian crit. (BIC)		-5.289	
PE	Coef.	Std.Err.	t-value	p-value	[95% Conf Interval]	Sig
Firm Size	-7.179	2.46	-2.92	.005	-12.121 -2.238	***
Square Firm Size	.244	.083	2.94	.005	.078 .411	***
Sales/ME	.064	.018	3.64	.001	.029 .1	***
Age	.008	.003	2.76	.008	.002 .014	***
Constant	53.138	18.209	2.92	.005	16.564 89.712	***
Pseudo r-squared	2.099		Number of obs		54	
Chi-square	65.783		Prob > chi2		0.000	
Akaike crit. (AIC)	-22.438		Bayesian crit. (BIC)		-10.504	

Note: \*\*\*  $p < .01$ , \*\*  $p < .05$ , \*  $p < .1$ .

and make better use of scale economies through better branding and use of market information. Furthermore, large firms have higher bargaining power in sales and resource procurement, better quality control, and more cost-effective equipment, which help firms realize their economic potential and display improved efficiency. In the current scenario, firms with smaller total assets are more efficient. The findings corroborate with the results of Saranga and Phani (2009), Mahajan et al. (2018), and Pannu et al. (2011). Additionally, age was a significant positive contributor to pure efficiency (Table 8). Older companies possess important experience gained from first-mover advantage and learning by doing, thus contributing to greater efficiency. Finally, the outcomes did not find any confirmation of a significant impact of COVID-19 or the war in Ukraine on the efficiency of pharmaceutical firms.

**Table 9.** The trends in returns to scale of Ukrainian pharmaceutical firms

Year	Returns to Scale			Firm count
	Constant	Decreasing	Increasing	
2018	3	2	4	9
2019	3	3	3	9
2020	2	1	6	9
2021	2	0	7	9
2022	2	6	1	9
2023	3	0	6	9
Total	15	12	27	54

The summary of Table 9 represents a year-wise distribution of firms according to returns to scale. The results of the study point to the fact that during 2018–2019, the distribution of firms across different returns was proportionate. As the country entered the phase of the COVID-19 pandemic in 2020–2021, 67–77% of top producers experienced

increasing returns to scale. Such results imply that Ukrainian manufacturers urgently need to increase the size of their business to achieve constant returns to scale. Business operations can be expanded through mergers and acquisitions with smaller domestic firms, foreign partnerships, or organically – through capital investments in man-

ufacturing and distribution facilities. The number of companies doing business under constant returns to scale has been relatively stable. In summary, during the last six years pharmaceutical market in Ukraine has transformed itself from a place that can accommodate all types of companies to an industry dominated by increasing returns to scale.

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## CONCLUSION

This paper aims to estimate the technical efficiency of Ukrainian pharmaceutical firms and test its determinants, particularly marketing expenditures and marketing productivity metrics along with firm size, age, COVID-19, and war effects, using a 2-stage input-oriented data envelopment analysis and Tobit regression. The study of technical efficiency revealed a decline in overall, pure, and scale efficiency during COVID-19 and the Russia-Ukraine war, although the decline was not statistically significant. Additional optimization (minimization) of marketing and sales expenditures is vital for the business success of pharmaceutical companies. Around 67% of the firms from the sample demonstrated a clear pattern of increasing returns to scale, implying the need to expand operations through internal resources or mergers, acquisitions, and partnerships with smaller market players. Smaller and older firms are more efficient and, hence, can better manage inputs. Thus, the study of efficiency between 2018–2023 found that big marketing budgets are detrimental to efficiency. Finally, firms need to increase the size of their operations to become more efficient.

This study has focused on finding reasonable arguments to align the company's financial and marketing goals when negotiating and managing cost allocation and the size of business operations. This study is limited to nine companies that openly provide financial data. The rest of the firms operate as limited liability companies; therefore, they are not legally obliged to publish their financial statements. Future research on efficiency should estimate a threshold of marketing expenditures that allow companies to be efficient, explore changes in the productivity of the pharmaceutical industry over the last two decades, and finally, study the effect of distinct advertising channels on technical efficiency. Given the industry's intense rivalry, revenue-maximization efficiency models can be implemented.

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